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A Literature Survey and Bibliometric Analysis of Application of Artificial Intelligence Techniques on Wireless Mesh Networks

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Abstract

Recent years have seen a surge in the use of technology for executing transactions in both online and offline modes. Various industries like banking, e-commerce, and private organizations use networks for the exchange of confidential information and resources. Network security is thus of utmost importance, with the expectation of effective and efficient analysis of the network traffic. Wireless Mesh Networks are effective in communicating information over a vast span with minimal costs. A network is evaluated based on its security, accessibility, and extent of interoperability. Artificial Intelligence techniques like machine learning and deep learning have found widespread use to solve a range of challenging, real-world problems. These techniques are well known for their ability to detect issues or patterns in traffic along with advancements in computing capabilities. Extensive research is being carried out to improve the performance of Wireless Mesh Networks. This survey aims to provide a disinterested overview of the application of different artificial intelligence techniques to enhance network performance. We focus on approaches that address the three fundamental problems in networking: traffic prediction, traffic routing, and congestion control. Our paper also includes the bibliometric analysis of the literature, highlighting the ongoing efforts in terms of statistics across multiple metrics. This survey aims to provide researchers in this community with a reliable compendium to get a brief yet succinct understanding of the current progress in the domain.

Index Terms

Wireless Mesh Network, Deep Learning, Machine Learning, Network Prediction, Adaptive Routing, Congestion Control

I. Introduction

Wireless mesh networks are an interconnection between devices or nodes that link or exchange the information to each other. Wireless mesh networks span the network connection over a larger area. Such networks are thus created by linking wireless access points located at the location of each network client.

Mesh nodes are small radio transmitters. They behave in the same manner as that of the wireless router. The software installed at these nodes ensures the communication and controls the interaction among these nodes over the network. The nodes automatically select the fastest and safest route in a dynamic routing process [1]. Wireless mesh routers interact in a multi-hop fashion, creating a reasonably stable network. Fig. 1 indicates a sample wireless mesh network. We see that clients connect to the routers using a wireless link. Each router performs data relaying for other mesh routers in the network, thereby following a traditional ad-hoc networking paradigm. Some mesh routers also have the additional capacity to act as Internet Gateways.

Wireless Mesh Networks are economical as they require fewer wires to establish a network, particularly for covering larger areas, thereby reducing the cost. The size of these networks grows proportionate to the number of nodes joining the network. Wireless Mesh networks follow self-configuration, where we can add a new node to an existing setup without requiring manual supervision or violation of the network constraints. They are also known to be self-healing i.e. the network determines the most optimal and fast route for sending data by itself in cases where any of the nodes is down or there are no active links in any of the networking routes. Wireless mesh nodes are thus easy to be created or removed. The networks are quite adaptable and easy to expand [1].

In computer science, adaptability refers to the extent to which an interactive system can adapt or inherit its behavior to individual users based on the information acquired about their behavior and environment [2]. Network adaptation includes adaptation in various aspects of the network. Various utilities required for the smooth functioning of a network include the prediction, categorization, and path routing of network traffic. Other factors include the management of various network resources, errors, and faults. The performance of a network is defined by the Quality of Experience (QoE), the Quality of Service (QoS), and the level of security [2].

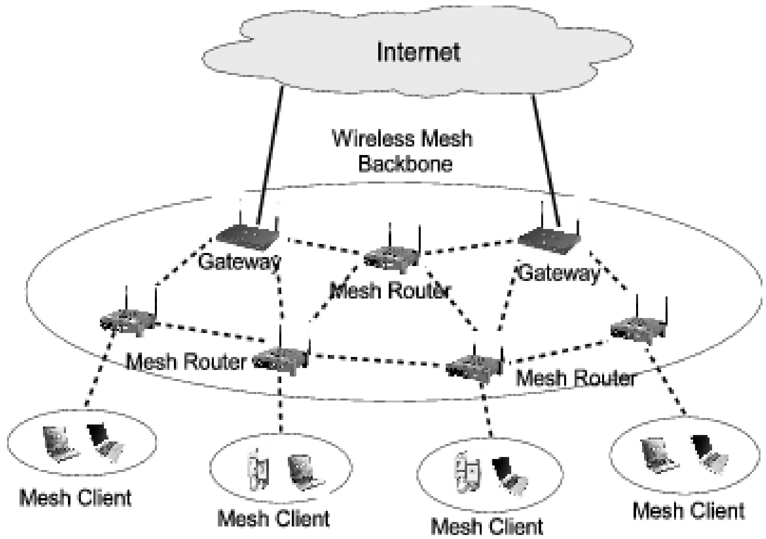

Fig. 1: Wireless Sensor Network

It is a must to build networks that have the ability of self-maintenance and self-healing. These networks would optimize and protect themselves and could easily recover from faulty situations. For monitoring the network, network traffic analysis has become more vital and essential in the present day. It would also ameliorate the financial challenges and improve the reputation of network providers, often violated by faults in the network [3], [4]. However, owing to the uniqueness of each network, a programmed solution that is successful in solving the problem for one network may not be suitable for another network of different patterns. Thus, a generalized solution is the need of the hour.

Host networks have risen significantly due to the higher switching capabilities of the Internet. The routers are having stronger radio links and enhanced hardware implemented in mobile enterprise backbone networks. These multifaceted networks face several challenges that include network traffic control, network maintenance, and efficiency or performance of the network [5], [6]. Due to the ever-increasing growth of computer hardware, coupled with the rise in massive and diverse social networking applications and services, the packets switched networks are observing a vociferous rise in data traffic. The comprehensive network solutions are not sufficient to accommodate the fluctuating network circumstances that might result from the massive growth of network traffic. It is the appropriate time to reconsider the enhancement of the management of network traffic.

Presently, Artificial Intelligence (AI) methods including Machine Learning (ML) and Deep Learning (DL) have found widespread application in a variety of areas and disciplines [7]–[10]. ML involves a set of algorithms that can be used to develop a model which ”learns” the patterns from the given dataset to complete a task objective. Rather than being explicitly programmed, it builds an algorithm by learning from the dataset to which it is exposed [2], [11], [12]. Machine Learning algorithms learn from the information presented to them and acclimatize to a varying environment, even in the case of wireless networks [4]. The benefit of using deep learning is the ease with which it can handle vast and complex data.

Recent years have seen increased efforts to create intelligent wireless networks. The focus has been on networks where the area is too big, with an extensive topology and challenging network scenario. DL techniques are used to find various network performance controlling parameters such as available hotspots, presence and distribution of interference, points of congestion, traffic bottlenecks, and availability of spectrum. It is preferred to use these methods as the complexity of wireless networks is too high with varying quality of links and dynamically changing states thereby making it difficult to program a fixed logic. Further, the involved network parameters like loss rate, link signal-to-noise ratio, and delay keep changing. It is desirable to have a smart modeling method [7], [13].

Artificial intelligence methods are suitable for networking due to multiple reasons:

- Classification and prediction algorithms in AI are basic but efficient algorithms that can be applied to solve network problems where the prediction of the network performance is a primary concern.
- AI also performs well in decision making, which can play a vital role in network scheduling and parameter adaptation based on the present state of the environment [14].
- It is tough to derive an accurate analytical model to represent intricate system behaviors consisting of the dynamic patterns of data [15], [16] and the associated throughput characteristics. However, AI techniques can derive these patterns easily.
- AI provides a plethora of options to build a comprehensive model that has a uniform training method.

This paper presents a survey of the application of AI techniques in the domain of wireless mesh networks. Specifically, we focus on the previous applications of methods in the three main factors related to these networks: traffic prediction, traffic routing, and congestion control. We present a disinterested analysis of the previous work while also throwing some light on the bibliometric analysis of the efforts done till now. Our main contributions through this paper are as follows:

- A comprehensive survey of the application of AI techniques to solve the three main problems of wireless mesh networks i.e. traffic prediction, routing, and congestion control.
- An unbiased analysis of the previous works in this domain which can prove to be a compendium for researchers to understand the perspective and shortcomings of the progress done till now.
- Bibliometric survey to highlight the nature and characteristics of the work done in this area in recent years.

The rest of the paper is structured as follows: Section 2 provides a brief review of machine learning and AI. Section 3 elaborates our survey in detail with a focus on the three application areas in wireless mesh networks. Section 4 shows the insight into our bibliometric survey while we present the conclusion of our work in Section 5.

II. AI and Machine learning: Overview

The term "Machine Learning" (ML) was coined by Arthur Samuel in 1959 as "the field of study that enables computers to learn without explicit programming" [17], [18]. ML methods can be segregated into four main types: classification, regression, clustering, and rule extraction. Classification focuses on labeling a given sample into one of the predefined class types. Regression tries to derive a relation between the dependent and independent variables used to predict the value of the dependent variable for a new sample. Clustering groups together similar data points based on the distance between them in the feature space. Rule extraction aims to establish statistical relationships in data. Problems in networking belong to one of these types. Therefore, the application of the strong capabilities of AI and ML algorithms for unscrambling the challenges in networks can prove to be a beneficial approach [19].

Machine learning can provide new opportunities for generalized model creation through a standardized method of training [15]. ML algorithms can be segregated into three types of learning: supervised, unsupervised, and reinforcement [17]. Supervised learning builds a model from labeled data and is useful in tasks like classification or regression. Unsupervised learning focuses on exploring patterns and clustering the given raw data. Reinforcement learning focuses on a reward-based approach where the agents learn from the environment and choose the series of actions that provide them with the highest reward.

DL techniques have even outperformed human beings for some errands for problems involving classification, regression, and decision making [3], [17]. Transfer Learning, Transformers, Attention mechanism, and Generative Adversarial Networks (GAN) are the recent trends that have been effective and efficient in solving real-world tasks for different applications in a range of domains. Deep Learning applies neural network layers to fetch information or extract the features from high dimensional raw and complex data, analogous to the working of the human brain. Deep Learning is a reasonable approach for network operators to design and operate their networks with additional intelligence and autonomy [2], [5]. Deep Learning algorithms output adaptive models to characterize high-level data abstractions.

The integration of intelligence into network traffic control systems plays a significant part in providing the quality of service (QoS) in Internet Protocol (IP)-based networks [15], [20]. AI techniques have been used over the past few decades to intelligently manage the network traffic and ensuring the control of traffic in both wired and wireless networks [21]. We describe this work in detail in the next section.

III. Application areas in Wireless Mesh Networks

We present the survey by first segregating the work based on the three main application areas: traffic prediction, traffic routing, and congestion control. Later, we describe the principal approaches used for improving network adaptation.

A. *Traffic prediction*

Predicting network traffic involves predicting the potential traffic volumes in the network. Traditionally, researchers used time series forecasting (TSF) to tackle this problem. TSF's main objective is to develop a regression model that can accurately predict future traffic volume based on the series of incoming data. This prediction is based upon the previously observed data, that constitutes the traffic volumes. Present traffic prediction TSF models fall into two major categories: the ones based on the statistical analysis approach and others that are developed by applying machine learning algorithms. The models based on the statistical approach are computed by analyzing the Auto-Regressive Integrated Moving Average(ARIMA) method [22], whereas most of the traffic prediction based on ML is based on supervised neural networks [3], [21].

The ARIMA model is the most commonly used TSF approach. In TSF, the moving average (MA) and autoregressive (AR) models are implemented in pairs to accomplish autoregression on distinguished and static data. However, because of the growing network size and subsequent increase in the network traffic density, the traditional TSF models are failing to deliver the best performance. Due to this, there has been an emergence of sophisticated ML models that are more suitable to handle such complex data. Of late, deterministic efforts have been explored to minimize operational overhead and improve traffic prediction accuracy by using features of the data stream, instead of relying on the traffic volume [23]. As compared to the TSF methods, traffic forecasting as a non-time series forecasting (Non-TSF) problem can be modeled using other approaches and characteristics [22], [24]. Similarly, instead of depending only on the traffic volume, efforts have been made to create a frequency domain-based model for network traffic streams [25]. The emphasis is on forecasting incoming and outgoing volumes of traffic on a link between data centers controlled by the flow of elephants.

B. Traffic routing

In networking, network traffic routing is an important task. Routing means choosing a route/path for the packet transmission. The criteria to select the route depends primarily on functioning strategies and the objectives like cost minimization, optimized use of connections, and the level of QoS. Routing algorithms must have the capacity to handle and cope up with complicated and dynamic network topologies. Such algorithms need to have the capability to understand the relationship between the chosen route and the planned QoS and the capability to predict the after-effects of routing decisions [26]. In the prevailing literature, Reinforcement Learning (RL) has been the most outperforming technique for selecting the paths i.e. routing [27]. In RL, learning agents explore the surrounding environment with no supervision, usually described as a finite-state Markov Decision Process (MDP), and learn from trial-and-error the best-suited course of action that maximizes a cumulative reward [27]. From the late 1990s and early 2000s, multiple research efforts on routing have been based on Q-learning and have suggested enhancements in the algorithm. Q-learning is one of the RL techniques, which is a model-free learning algorithm. The main aim of Q-learning is to tell an agent what to do under the given circumstances. This outcome is the outcome of the rule that the algorithm has learned. In Q-learning, the algorithm constitutes its logic for the following reasons:

- To develop a methodology to improve the efficiency of Q-routing to increase learning and the speed of convergence
- To make use of lower operational complexity to develop algorithms that are unique to each network. For example, networks with constraints on energy or on routing paradigms (multicast routing) [27].
- To increase the coordination between the training routing agents to meet the diverse global performance requirements [3], [27].

The single-agent RL model gives local optimization irrespective of global performance. Hence, a single-agent RL model is not enough to obtain global optimizations like the maximization of the lifetime of the network or to provide network-wide QoS.

Multi-Agent Reinforcement Learning (MARL) guarantees that each node shares its self-information (state information, Q-value, reward). MARL also ensures that nodes share their conclusion with the surrounding nodes in the network to attain comprehensive optimization, along with gaining information about their environment. In this method, the nodes responsible for selecting the routing policy also monitor the impact of their neighbors and other connections on the result. As a result, this method is complex and time-intensive. A state is acquired by the system, which is a current or cumulative state of all the learning agents. The resultant output i.e. the action or set of actions is the combined action of all the network agents and is derived by a reasonably intricate process [28]. These methods differ in terms of the way they disseminate the learning ability and the level of multiple learner associations present in them. Different approaches offer different network topologies and more natural utility functions. Nonetheless, while implementing MARL, there is a need to strike a balance between the benefits and overhead, especially for networks that have constraints on the utilization or availability of the resources. This is also true for multifaceted wireless networks where collaboration is very much significant [13].

C. Congestion control

Congestion control is a significant aspect of networking. It ensures an uninterrupted and seamless journey and control over the number of packets traveling over the network. It also provides reliability to the network supported by the fair distribution and utilization of resources with an acceptable loss ratio of packets [6]. Various network architectures implement their own protocol sets for congestion control. The congestion control mechanisms implemented in TCP as very well known. The current Internet works on TCP along with IP. TCP congestion control processes operate in the end systems of the network to control the transmission speed of packets when congestion is observed. One more common congestion control mechanism is queue management, which operates within the network's intermediate nodes (e.g., switches and routers) to balance TCP [3]. Adaptive network designs and congestion control mechanisms that are effective for the Internet have been developed over many years. Delay-Tolerant Networks (DTN) and Named Data Networks (NDN) [29] are a few of them. Yet, there are inadequacies in some aspects, such as the detection of packet loss, queue management, congestion window update (CWND), and congestion extrapolation [27]. These issues can be ameliorated to improve the congestion control mechanism. There is much potential in applying ML to enhance congestion control. A notable issue with TCP is that all packet losses once are known, are treated as network congestion, due to the buffer overflow.

Consequently, other issues like reordering packets, fading, scattering, and shadowing in wireless networks would render the implementation of congestion control useless owing to packet loss and modification in the state [17]. As a result, TCP decreases its transmission rate unnecessarily, at every single observed packet loss, reducing end-to-end control of the bandwidth in different networks. Therefore, TCP throughput for wireless networks can be increased by correctly determining the cause of packet loss and lowering the rate of transmission whenever congestion is observed [24], [30]. Currently, there is no method for TCP congestion control to identify the cause of the packet loss.

D. Network adaptation techniques

There has been a continuous investigation of many solutions developed using ML and DL for packet loss identification in systems based on cellular-wireless, wired, and optical networks. By using supervised binary classification ML algorithms, we can train the identifier model offline. Generally, these techniques use existing metrics at the end-system and test their classifier on the data generated using network simulators. Researchers use simulators like NS-2 for generating these data points, also known as synthetic data.

Queue management is a system that complements TCP congestion control mechanisms in the network's intermediate nodes. If appropriate, queue management is responsible for dropping packets to control the queue length in the transitional nodes. The standard strategy for managing the queue is dropping the packets at the tail of the queue. The First-In-First-Out (FIFO) policy is applied to coordinate the queue-entry of the packets. Every queue in Drop-tail sets a maximum length to accept the incoming packets. The packets arriving after the queue is full are removed, and once the queue is available, the packets are allowed to enter the queue [31]. These methods contribute to the synchronization of TCP. However, the combined use of these two can introduce three main issues:

- Due to the simultaneous decrease in TCP rate and redundant link usage, there is an unnecessary loss of packets.
- Because of a constant full queue status, there is an increase in the queuing lag.
- Few connections that monopolize the queue space cause the misuse of the TCP mechanism.

Active Queue Management (AQM) mitigates the Drop-tail's limitations by discarding packets before filling the queue, thus being a proactive approach. With this approach, the end-systems react before the queue overflows to congestion, and the intermediate nodes handle the dropping of packets.

Another popular and earlier AQM system is Random Early Detection (RED) [32]. RED continuously adjusts the likelihood of dropping (marking) to a predicted rate of congestion. This congestion rate is based on a predefined threshold value that is a function of the average queue length. However, RED suffers from poor responsiveness and does not stabilize the queue length to an expected value. Its efficiency in terms of the use of links and drop of packets depends heavily on parameter tuning. This stabilization of queue length is yet to be tackled successfully [15]. The involved parameters are less sensitive to the time and nonlinear conditions of the network. Therefore, extensive research efforts are being put into utilizing the capabilities of ML algorithms to develop an intelligent and robust AQM scheme. This helps for effective queue length management and adjustment of various control parameters as per the network and traffic circumstances. In AQM, different supervised techniques are applied to time series forecasting (TSF) and methods based on reinforcement to judge the reason behind the increase in the probability of packet drop.

Proactive Queue Management (PAQM) is one of the techniques whose operations depend on such predictions. PAQM has improved the risk of dynamically dropping the packet [25]. Another significant TCP variable, CWND (Congestion Window) per-connection state is announced across the network. It helps gain control over the receiver to transmit the amount of data before it receives an ACK signal. Another state parameter is the Receiver Window (RWND), which governs the volume of data that the receiver communicates or advertises to the sender to determine the amount of data the receiver can receive. The congestion control mechanisms of TCP calculate the average of these two variables CWND and RWND values for determining how much data can be let into the network [3]. Thus, TCP unnecessarily lowers the rate in wireless loss links by increasing CWND after each packet loss observed, which adversely affects the end-to-end efficiency. Besides, TCP's CWND upgrade method is not appropriate for the other characteristics of different network technologies. It is due to variation in the bandwidth, storage capacity, and limitations on the battery power. The existing complexities of the network can also exacerbate the situation. Further, TCP's determinist design tends to be a basis for higher losses of connection and CWND synchronization problems in WANET where node flexibility continually adapts multi-hop wireless paths [3]. Some TCP variants have been proposed to resolve these limitations, such as TCP-Vegas [31] and TCP-Westwood [33].

RL-based solutions have been suggested to resolve the issues related to updating CWND (or sending rate) under the given network circumstances. Some of these solutions are designed specifically for networks that have constraints on the resources, like WANETs. On the other hand, the other techniques consider a larger span of network architectures, such as mobile satellites and data center networks [33]. Unless stated otherwise, the RL trains the network's end-systems online in a dynamic way to assess the increase for CWND updates. Some methods use the same technique as that used in the RL technique; however, they differ either like the output, i.e., set of action (i.e., finite or continuous) or the design method used [22], [29].

The network protocols adapt their policy based on the assessment of parameters in the network that enable the inference of the congestion state. The traditional methods for calculating these network parameters remain unreliable as they do not clearly understand the relationships between the different parameters. For example, the quantitative and historical models used by TCP to calculate the Exponential Weighted Moving Average (EWMA) and the round-trip time (RTT) is not reliable with complex data [15], [32]. ML-based solutions addressed congestion limitations in different network architectures. ML algorithms estimate different network parameters such as bandwidth, RTT, mobility, NDN table entry speed, and DTN congestion level in TCP-based networks.

Most of these initiatives use different supervised learning techniques often for predictive purposes. Researchers have also suggested another method of estimating TCP throughput. In this technique, the ML solution resides in a WLAN's access point rather than the end-systems. Another method used in Bayesian Networks is the creation of a Directed Acyclic Graph (DAG). The DAG consists of a probabilistic model with multiple features that help to predict throughput. By using a subset of inference functions, a simplified probabilistic model can be developed from the built DAG. The Bayesian Network model's training and testing are performed on synthetic data collected from simulators like NS2 [22]. Results show that this model produces only a small prediction error when exposed to the right amount of training data, around 1000 samples. Besides, researchers have shown that the prediction is based on the number of MAC transmissions (MAC-TX). This results in a similar or occasionally lower value of inaccuracy when the full set of features are available for training and testing [3].

TCP incorporates the most common congestion control mechanism in the modern Internet. TCP degraded the network's bandwidth when the packet errors were triggered for non-congestion reasons. Therefore, identifying the cause of the failure of the packet can improve the TCP throughput. Machine learning methods are used to resolve different management and development issues based on the appropriateness of specific technical and network parameters. For the most part, reinforcement learning (RL) is applicable in the wireless mesh network to address model optimization issues. Many machine learning algorithms are used in wireless mesh networks. The commonly used supervised learning algorithms are Support Vector Machines (SVM), Decision tree (DT), Artificial Neural Networks (ANN), Perceptron models, and Bayesian models.

The most commonly used unsupervised learning methods are K-means and Principal Component Analysis (PCA). Reinforcement learning methods include Q-Learning, Learning Automata (LA), and Markov Decision Process (MDP). K-Means methods can be used to resolve the issues in the allocation of the channel in wireless mesh networks. ANN, MDP machine learning methods are ideal for solving the routing problems in wireless mesh networks. To improve fairness in WMNs MDP, Q-Learning has been used [32]. Q-Learning, LA, Bayesian technique is appropriate for the rate adaption problem. K-Means approach is used to handle fault detection problems [22], [30], [31]. There are other ways in which network adaptation problems are dealt with. In Q-Learning: Q-value Q (s, a) is correlated with the output action 'a' at a state that is changed every time the action is performed during route determination. Whereas in Learning Automata (LA), learning automata-based mechanisms are in use for route optimization. Other algorithms like Distributed Learning Automata-based Multicast Routing Algorithm (DLAMRA), Learning Automata-based Multicast Routing (LAMR), Steiner Connected Dominating Set (SCDS), etc. make an optional route from origin to destination using the learning automata principle. Artificial Neural Networks (ANN) is one of the most effective techniques for making a routing decision. To predict the link and route failure possibility, the Cerebellar Model Articulation Controller(CMAC) algorithm is used [15], [34], [35].

In DL approaches, a layered neural architecture extracts the information(features) from input data and then determines the consequence of extraction [32]. In the DL processes, computers are required to learn from experiences and produce some learning models. Because of the comprehensive training process, the functional neural network architecture estimates appropriate weight values between neural nodes, that are capable of extracting the features from the data provided to them as input data. After the training process, it is possible to make a suitable decision to obtain a high reward [21], [36], [37]. The implementation of DL addresses the following questions [38], [39]:

- How to describe the system status using appropriate numerical formats at the input layer of the DL network? [40]
- How to characterize or infer the output layer of the DL network? [7], [41]
- How to estimate or change the reward value and the nature of the reward function? [42]
- The architecture of the DL system, including comments on the number of hidden layers, layer designs, and layer connections [13], [20].

IV. Bibliometric survey

A bibliometric survey is an analysis that helps us understand the trends from the point of literature, published about the topic. With a bibliometric approach, we get a great insight into the ongoing as well as past literature available in a graphical way. There are various databases like Web of Science and Scopus that provide these bibliometric values for a given domain. In this survey, for the analysis of the literature on prediction techniques used in the wireless mesh networks area, we refer to the Scopus Database [43]. The database is categorized into two parts: Open Access Journals' database and Paid Journals Database. The database used for analysis was accessed in August 2020. The primary keywords used for the survey were "Prediction" and "Wireless Mesh Networks". We present the bibliometric survey by first segregating the work into three main areas: traffic prediction, traffic routing, and congestion control. It is followed by an overall review of the trends seen in the research of wireless mesh networks.

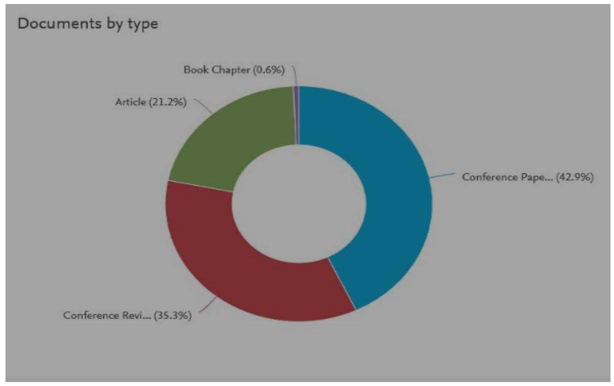

Fig. 2: Traffic prediction documents by types

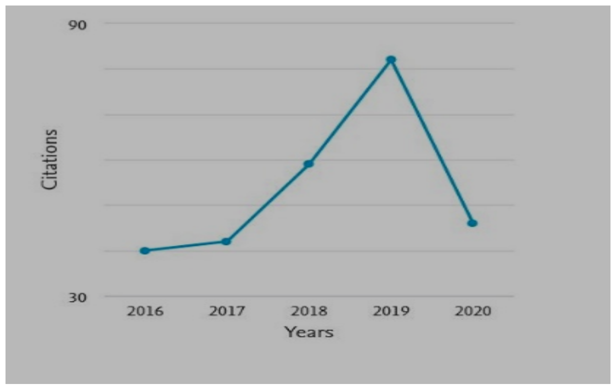

Fig. 3: Traffic prediction document citations by year

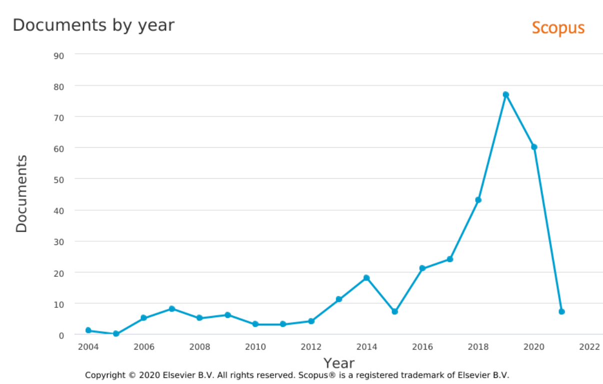

Fig. 4: Traffic prediction documents by year

A. *Traffic prediction*

It can be seen from Figure 2, that the literature related to traffic prediction in wireless mesh networks can be found in three categories namely, articles in book chapters, conference review, and Conference papers.

It can be known from Figure 3 that the research on the prediction of network traffic is ever increasing with the rise in citations. Figure 4 shows the literature publications per year whereas Figure 5 shows the research articles by their source.

B. *Traffic routing*

We find various insights related to traffic routing as shown in the diagrams below. It can be seen from Figure 6 that the literature related to traffic routing in wireless mesh networks has been affiliated with various universities. Figure 7 shows the segregation of documents into three main categories, namely book chapters, conference papers, and reviews.

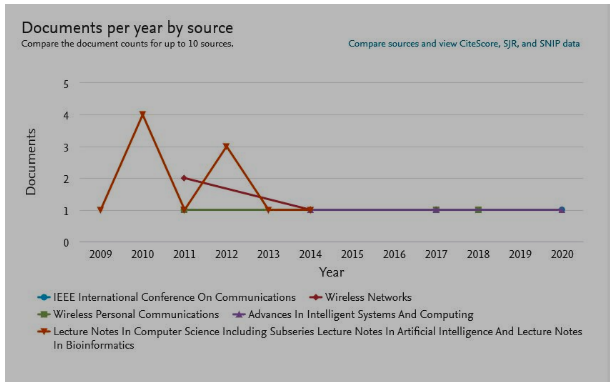

Fig. 5: Traffic prediction documents by source

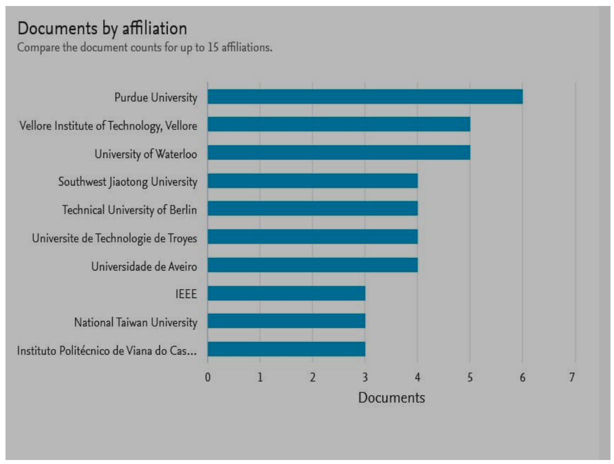

Fig. 6: Traffic routing documents by affiliation

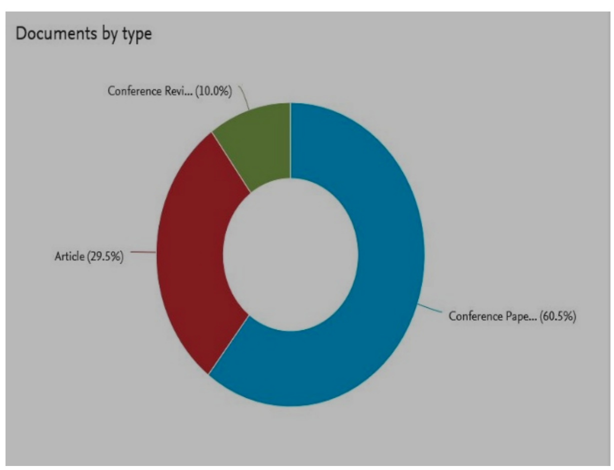

Fig. 7: Traffic routing documents by types

Figure 8 shows the literature related to the routing in wireless mesh networks published per year. It can be known from Figure 9 that the research on the routing of network traffic is going on in almost all well-known countries in the world.

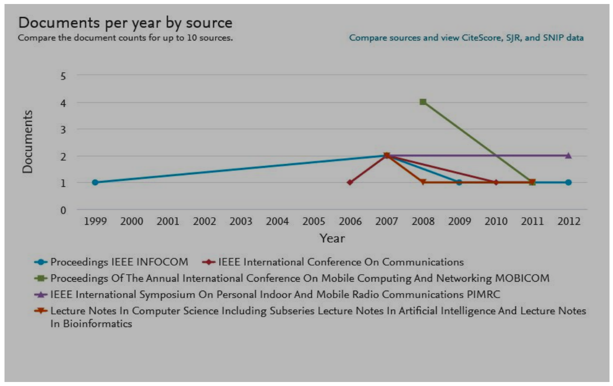

Fig. 8: Traffic routing documents by year

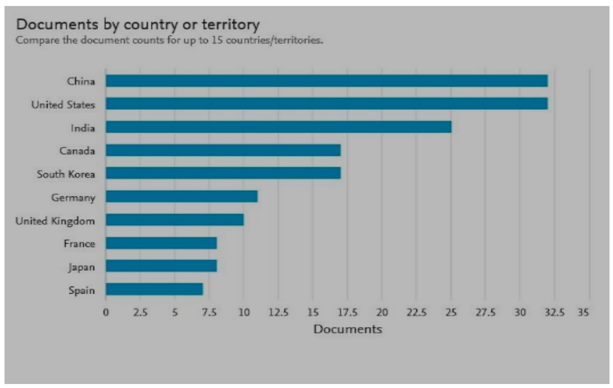

Fig. 9: Traffic routing documents by country

C. Congestion control

Detailed insights about the literature are shown in the diagrams below. We can see from Figure 10 that the affiliation of the literature related to congestion control in wireless mesh networks is with various universities. Figure 11 highlights the number of documents published by years.

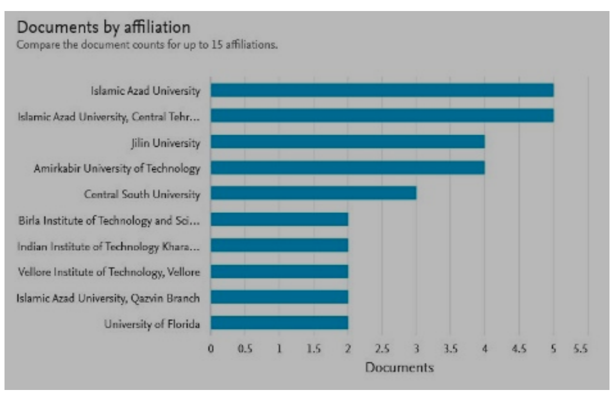

Fig. 10: Congestion control documents by affiliations

D. Trends in Wireless Mesh Networks

We also present the trends that are observed in the overall research efforts being made by the community in the area of wireless mesh networks. These include observations about the geographical regional analysis, trends for yearly publishing, trends by language, and the keyword statistics.

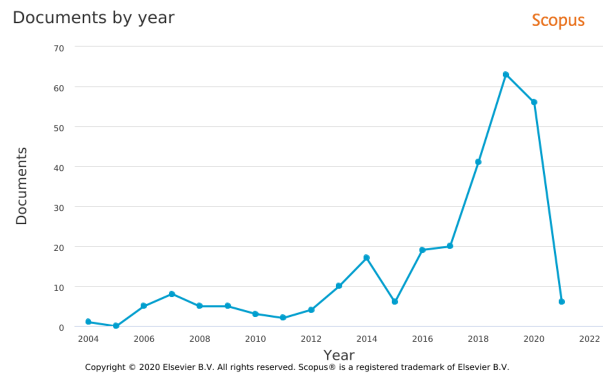

Fig. 11: Congestion control documents by year

Fig. 12: Geographical analysis of work done in wireless mesh networks

Figure 12 shows the geographical analysis in terms of the research being done in the various regions of the world. It can be seen that significant work is being done in European countries along with South-East Asia. The fact that noteworthy contributions have been made from every region worldwide are promising signs for the community.

Further, in terms of the linguistic and frequency trends observed, we tabulate down the data. Table I shows the number of research papers in this domain based on their language. It should be noted that most of the work in this domain has been published in English. The accessibility to research is thus more widespread. The yearly trends are shown in Table II and a decline in the work has been observed year over year.

Language	**No. of papers**
English	810
Chinese	23
French	17

TABLE I: Research trends by language

Year	**No. of publications**
2015	188
2016	170
2017	126
2018	142
2019	114
2020	69

TABLE II: Yearly trends in research

Finally, we also present the Top 20 most occurrent keywords when searching for wireless mesh networks in the Scopus database. This list is also accompanied by a diagram indicating the most frequent keywords. It can be seen that the most dominantly occurring keywords are mesh networks, wired networks, and other network-related jargon.

Selected	Keyword	Occurrences	Total link strength
✓	mesh networking	634	3308
✓	wireless mesh networks (wmn)	506	2857
✓	mesh generation	504	2788
✓	wireless mesh networks	209	1130
✓	network routing	156	1030
✓	wireless mesh networks (wmns)	143	876
✓	quality of service	109	709
✓	wireless mesh network	130	666
✓	routing protocols	84	535
✓	mobile telecommunication systems	74	505
✓	gateways (computer networks)	72	453
✓	wireless telecommunication systems	71	438
✓	optimization	67	424
✓	internet protocols	63	422
✓	channel assignment	70	399
✓	algorithms	55	364
✓	wireless networks	57	314
✓	complex networks	45	301
✓	bandwidth	50	298
✓	routing	50	297

Fig. 13: Keyword statistics of papers in Wireless mesh networks

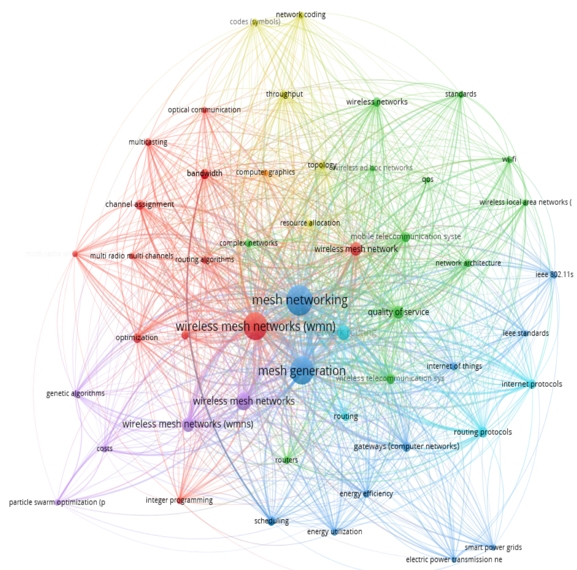

Fig. 14: Most frequent keyword diagram

V. Conclusion

In this survey, we focused on understanding the various approaches and previous attempts to improve the performance of Wireless Mesh Networks. The survey focused on network performance from the perspective of traffic volume, routing, and congestion control. While optimizing the network's performance, many decisions are expected to be taken in real-time, for example, the application of artificial intelligence for deciding the routing strategy. Similarly, identification of the reasons for packet loss and choice of the policy application in TCP can be automated. The network should be able to recall similar incidents from the past and try to apply its intelligence to produce the same behavior as it had done back during the incident. Dynamic and intelligent decision-making capacity is the primary concern in today's communication technology. Many adaptive aspects, such as congestion control, admission control, anomaly detection, and bandwidth allocation, require the fundamental and essential facts before predicting the network traffic. Intelligent route selection gives tremendous help in routing and path selection. The congestion control mechanism is applied to increase the throughput of TCP over wireless links. This is done to prevent the mechanism from reducing the transmission rate as observed when in link error loss. The application of AI techniques, i.e., the use of Machine Learning and Deep Learning techniques on humongous, heterogeneous data, improves the Wireless Mesh Network's performance to a greater extent.

Thus, the application of AI techniques is becoming a default approach to improve network performance. Predicting network traffic involves predicting potential traffic volumes and has traditionally been tackled by time series (TSF) forecasting. From the referred literature, SVM and the Autoregressive Integrated Moving Average (ARIMA) model are combined for the prediction of traffic volume of mobile traffic over extended time frames. The combination of Conv. LSTMs and 3D CNNs are a powerful way to construct Spatio-temporal neural networks. This combination captures the complicated Spatio-temporal features spread at a large scale. For Routing in WMN, the Application of Deep Learning helps in improving the adeptness of routing decisions. Reinforcement Learning has dominated as one family of ML techniques for routing. For congestion control in WMNs, a Variable Order Markov (VOM) prediction model is used to predict the congestion status in each link in the network to identify new routes and adjust transmission rates.

Hence we have provided a detailed walk-through of the different AI techniques applied to Wireless Mesh Networks for traffic prediction, adaptive routing, and congestion control. This survey focused on the adaptations required to improve the performance of Wireless Mesh Networks. There are many other aspects like QoE management, Fault Management, QoS, and Network Security, where artificial intelligence techniques can be applied to improve the wireless mesh network's performance. Future work would include improvements in this area to enhance the overall functionality of the network.

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